COPY 2 of 2 copies
SERIES C

AD-A240 989

IDA PAPER P-2022

EXTENDING THE CNVEO SEARCH MODEL TO THE MULTITARGET ENVIRONMENT

Stanley R. Rotman
Marta L. Kowalczyk

June 1987

Prepared for
Office of the Under Secretary of Defense for Research and Engineering

91-12059

INSTITUTE FOR DEFENSE ANALYSES
1801 N. Beauregard Street, Alexandria, Virginia 22311

IDA Log No. HQ 87-32236

DEFINITIONS

IDA publishes the following documents to report the results of its work.

Reports

Reports are the most authoritative and most carefully considered products IDA publishes. They normally embody results of major projects which (a) have a direct bearing on decisions affecting major programs, or (b) address issues of significant concern to the Executive Branch, the Congress and/or the public, or (c) address issues that have significant economic implications. IDA Reports are reviewed by outside panels of experts to ensure their high quality and relevance to the problems studied, and they are released by the President of IDA.

Papers

Papers normally address relatively restricted technical or policy issues. They communicate the results of special analyses, interim reports or phases of a task, ad hoc or quick reaction work. Papers are reviewed to ensure that they meet standards similar to those expected of refereed papers in professional journals.

Memorandum Reports

IDA Memorandum Reports are used for the convenience of the sponsors or the analysts to record substantive work done in quick reaction studies and major interactive technical support activities; to make available preliminary and tentative results of analyses or of working group and panel activities; to forward information that is essentially unanalyzed and unevaluated; or to make a record of conferences, meetings, or briefings, or of data developed in the course of an investigation. Review of Memorandum Reports is suited to their content and intended use.

The results of IDA work are also conveyed by briefings and informal memoranda to sponsors and others designated by the sponsors, when appropriate.

The work in this document was conducted under contract MDA 903 84 C 0031 for the Department of Defense. The publication of this IDA document does not indicate endorsement by the Department of Defense, nor should the contents be construed as reflecting the official position of that agency.

This paper has been reviewed by IDA to assure that it meets high standards of thoroughness, objectivity, and sound analytical methodology and that the conclusions stem from the methodology.

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION: UNCLASSIFIED	1b. RESTRICTIVE MARKINGS
2a. SECURITY CLASSIFICATION AUTHORITY: NA	3. DISTRIBUTION/AVAILABILITY OF REPORT: Approved for public release; distribution unlimited.
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE: NA	
4. PERFORMING ORGANIZATION REPORT NUMBER(S): IDA Paper P-2022	5. MONITORING ORGANIZATION REPORT NUMBER(S)
6a. NAME OF PERFORMING ORGANIZATION: Institute for Defense Analyses; 6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION: DoD-IDA Management Office, OUSDRE
6c. ADDRESS (City, State, and Zip Code): 1801 N. Beauregard Street, Alexandria, VA 22311	7b. ADDRESS (CITY, STATE, AND ZIP CODE): 1801 N. Beauregard Street, Alexandria, VA 22311
8a. NAME OF FUNDING/SPONSORING ORGANIZATION: OUSDRE (R&AT); 8b. OFFICE SYMBOL (If applicable): MST	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER: MDA 903 84 C 0031
8c. ADDRESS (City, State, and Zip Code): The Pentagon, Washington, DC 20301-3071	10. SOURCE OF FUNDING NUMBERS: PROGRAM ELEMENT; PROJECT NO.; TASK NO.: T-D2-210 Subtask E; WORK UNIT ACCESSION NO.

11. TITLE (Include Security Classification)
Extending the CNVEO Search Model to the Multitarget Environment

12. PERSONAL AUTHOR(S).
Stanley R. Rotman, Marta L. Kowalczyk

13. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Final	FROM 11/86 TO 5/87	June 1987	52

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	search, target acquisition, combat, electrooptics, multiple targets, mathematical models, simulations

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

This paper develops a multitarget acquisition model as an extension of the single-target acquisition model of the Army's Center for Night Vision and Electro-Optics. The paper then outlines the implementation of the multitarget acquisition model in battlefield combat simulations. Finally, the paper suggests how the model may be used to simulate field tests accurately and how some simple experiments can validate the model.

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT: ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION: UNCLASSIFIED
22a. NAME OF RESPONSIBLE INDIVIDUAL: Marta L. Kowalczyk	22b. TELEPHONE (Include Area Code): (703) 578-2862; 22c. OFFICE SYMBOL

DD FORM 1473, 84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete

SECURITY CLASSIFICATION OF THIS PAGE
UNCLASSIFIED

IDA PAPER P-2022

EXTENDING THE CNVEO SEARCH MODEL TO THE MULTITARGET ENVIRONMENT

Stanley R. Rotman
Marta L. Kowalczyk

June 1987

INSTITUTE FOR DEFENSE ANALYSES

Contract MDA 903 84 C 0031
Task T-D2-210, Subtask E

FOREWORD

This paper was prepared under Task T-D2-210, Subtask E, for the Office of the Under Secretary of Defense for Research and Engineering, Research and Advanced Technology, Military Systems Technology, under the technical cognizance of Dr. John M. MacCallum, OUSDRE(R&AT/MST), and Dr. Herbert K. Fallin, Jr., Technical Advisor, Office of the Deputy Chief of Staff for Operations and Plans, U.S. Army (DAMO-ZD).

ABSTRACT

This paper develops a multitarget acquisition model as an extension of the single-target acquisition model of the Army's Center for Night Vision and Electro-Optics. The paper then outlines the implementation of the multitarget acquisition model in battlefield combat simulations. Finally, the paper suggests how the model may be used to simulate field tests accurately and how some simple experiments can validate the model.

CONTENTS

Foreword iii

Abstract v

SUMMARY S-1

I. INTRODUCTION 1

II. FIELD-OF-VIEW SEARCH 3
A. Overview of CNVEO Model 3
B. Multitarget Field-of-View Search Scenario--First Detection 5
C. Multitarget Acquisition--Multiple Detection 15
D. Summary 22

III. FIELD-OF-REGARD SEARCH 23
A. Overview of CNVEO Model 23
B. Multitarget Acquisition--First Detection 24
C. Multitarget Acquisition--Multiple Detection 27

IV. BATTLEFIELD MODEL 29
A. Basic Principles 29
B. Single-Target FOV Acquisition 30
C. Multiple-Target FOV Acquisition 31

V. FIELD TESTS AND EXPERIMENTS 37
A. Validating Experiments 37
B. Field Test Interpretation 39

VI. CONCLUSION 41

REFERENCES 43

SUMMARY

The search model of the Army's Center for Night Vision and Electro-Optics (CNVEO) is used by the U.S. armed services and those of several allied countries in the calculations of their battlefield models and for the interpretation of field test results. In this paper, we extend the model to the case of a single observer searching a field of regard in which several targets are present.

We first consider a single field of view in which a fixed number of independent targets are located. The expression for the cumulative multitarget acquisition probability is similar to that for single-target acquisition, $P(t) = P_\infty[1-\exp(-t/\tau)]$. The multitarget, single-glimpse acquisition rate is simply the sum of the single-target, single-glimpse acquisition rates. The derivation of the multitarget P_∞, the probability that a target will be acquired in essentially infinite time, is dependent on how one understands the existence of a nonunity P_∞ in single-target acquisition. The value of P_∞ may be due to the different number of observable cycles each member of a normal observer ensemble needs for target detection. Another possibility is that P_∞ is due to the unique interaction of each target image and the surrounding clutter in the mind of each member of the observer ensemble. A third possibility is that after a finite length of time, an observer ceases to search effectively because of either mental weariness or the repetition of features that attract the human eye. We show that how one interprets the cause of the single-target P_∞ affects the form of the multitarget P_∞. Calculations are done both for the case where we are only concerned with the

first target obtained and for the situation in which the detection of all targets present is desirable.

We then consider field-of-regard search. In the interest of simplification, the field of regard is considered to consist of several discrete fields of view; each field of view is randomly accessed for a fixed time T_0. Both the case where the number of targets in each field of view is known in advance and the case where the targets are randomly distributed through the field of regard are considered. Expressions similar to those used for single-target field-of-regard search are obtained.

Practical guidance for how this multitarget model could be implemented in a battlefield model is given in this paper. In addition, field tests that will validate the field-of-view and field-of-regard multitarget search model are suggested. This paper represents a logical and necessary extension of the CNVEO model to multitarget battlefield models and field tests.

I. INTRODUCTION

An understanding of the human target acquisition process has been of interest to researchers in industrial, academic, and defense-related settings. Despite advances made in understanding the operation of the eye and the physiological interaction between the eye and the brain, factors such as the search pattern used to scan a picture and the influence of clutter on the detection probability of a target are still treated empirically.

The search model of the Army's Center for Night Vision and Electro-Optics (CNVEO) predicts single-target acquisition probabilities for various search tasks using electro-optic devices.[1,2] The model computes the single-glimpse probability by considering the number of resolvable cycles across the target (the Johnson criteria); the number of resolvable cycles needed for detection, recognition, and identification is a function of the clutter level, input qualitatively into the model. The CNVEO model has been adopted by several of the U.S. armed services as well as allied countries, including Canada and Australia. Britain, where several model approaches are used, is a notable exception.[3] One British approach to search modeling explicitly uses a visual lobe, which is defined as the angle from the foveal axis at which the human eye can just detect a target. The CNVEO approach, on the other hand, uses a mean glimpse time, but it is possible in that approach to implicitly define a visual lobe. After such an assumption is made, the equations used in both the British and the CNVEO search models are similar.

While the CNVEO model itself is a single-observer, single-target model, it is used in modeling battlefield environments in which multitarget situations exist. This paper represents an attempt to expand the CNVEO model to multitarget conditions. We first consider a single field of view (FOV) in which several targets may be present. We then expand our consideration to field-of-regard search. Expressions similar to those used for single-target field-of-regard search are obtained.

Since the CNVEO model is semiempirical with regard to the number of line cycles needed for detection and the asymptotic probability of detection for long times, we must consider the assumptions that underlie the CNVEO model. In other words, this paper considers the CNVEO model to be correct in the single-target condition; nevertheless, understanding the driving factor in several of its empirical parameters is crucial for extrapolating the model to the multitarget case.

Practical guidance for how this multitarget model could be implemented in a battlefield model is given in this paper. In addition, field tests that will validate the field-of-view and field-of-regard multitarget search model are suggested.

II. FIELD-OF-VIEW SEARCH

A. OVERVIEW of CNVEO MODEL

The expression for the probability as a function of time P(t) of detecting a single target with field-of-view search is

$$P(t) = P_\infty [1 - \exp(-P_0 t / t_f)] \qquad (1a)$$

or

$$P(t) = P_\infty [1 - \exp(-t/\tau)], \qquad (1b)$$

where P_0 is the single-glimpse probability, t_f is the mean fixation time (assumed to be 0.3 seconds), τ is the mean acquisition time, and P_∞ is the fraction of the normal observer ensemble by whom the target can be found, given unlimited time. In the original formulation of this model, P_∞ is assumed to be equal to

$$P_\infty = \frac{(N/N_{50})^E}{1 + (N/N_{50})^E}, \qquad (2)$$

where

N = the number of resolvable cycles across the target

N_{50} = the number of cycles required for P_∞ to equal 0.5

E = 2.7 + 0.7 (N/N_{50}).

The number of resolvable cycles across a target, N, is equal to the product of the critical target dimension, usually chosen as the minimum overall dimension of the target from the observer's viewpoint, and the spatial frequency of the smallest target equivalent bar pattern that can be resolved through the viewing device. The number of resolvable cycles required for P_∞ to equal 0.5, N_{50}, is typically set equal to 0.5, 1, and 2 for low, medium, and high clutter, respectively.

The mean acquisition time τ is equal to 6.8 N_{50}/N. Since P_∞ equals approximately $N/2N_{50}$ for N/N_{50} less than 2, τ can be set equal to $3.4/P_\infty$ for those values of N/N_{50}. (Note that for large N the two expressions yield different values for τ. It is hypothesized that, in this case, the former value of τ should be used).

If one considers the case in which a single value for the glimpse probability (called P_0) exists, and independent glimpses are occurring at a rate $1/t_f$, the probability of detection as a function of time would be[4]

$$P(t) = 1 - \exp(-P_0 t/t_f). \tag{3}$$

This is the standard expression for the probability of the first arrival time for a Poisson process.

It is not intuitively obvious why the P_∞ term in Eq. 1 exists, although experimentally it is well established. Lawson et al.[1] attribute P_∞ to the distribution in the number of observable cycles each member of a normal observer ensemble needs for target detection. For any particular ensemble, there will be a subset of observers who will never find a target with that size and contrast. Thus, P_∞ is the fraction of observers who can find the target. (Of course, even within the subclass of people who can find the target there are those who have a higher-than-average glimpse probability and those who have a lower one; however, the model uses a constant glimpse probability P_0 for this group.) It should be noted that C.G. Drury[5] has attributed the existence of P_∞ not to a failure in the search process but to mistaken identification in a separate examination process. It can be shown that the conclusions we reach in this paper also apply to the Drury model.

If one assumes that each observer can be ranked by his perception ability, his detection of one target will be correlated with his ability to detect a second target, i.e., an observer who cannot observe a target with a higher effective value of P_∞ will never find a target with a lesser value of P_∞. We shall call this possibility Assumption 1.

Several other possibilities would explain the existence of a nonunity P_∞ in a realistic terrain. One possibility is that P_∞ is due to the unique interaction of the target image and the surrounding clutter in the mind of each member of the observer ensemble. Any particular target will be mistaken for a background object by some fraction of the observer ensemble. It should be noted that it is quite possible that someone who cannot detect an "obvious" target in realistic terrain (with a large number of resolvable cycles) may be able to detect a less-obvious target in a different orientation. We shall call this possibility Assumption 2.

Another possibility for the origin of P_∞ is that after a finite length of time, an observer ceases to search effectively because of either mental weariness or the repetitiveness of the search of features that attract the human eye. As time goes on, one ceases to search efficiently and, hence, if one has not acquired the target by then, one never does. We shall call this possibility Assumption 3.

Regardless of the reason why P_∞ exists, the single-target probability curves can nevertheless be fitted to an empirically observed P_∞. The same is true of the clutter level. The value of N_{50} should be a function not only of the general surroundings but also of the specific relationship of the target to the background as well as to particular objects within the background. (In a scene that is half forest and half grassy plains, the detectability of the target should depend on whether the target is in the forest or on the plains, even if the immediate contrast is the same in each case.) The fixing of a specific value of N_{50}

represents an expected average value of the effect that a specific amount of clutter should have on target detection.

B. MULTITARGET FIELD-OF-VIEW SEARCH SCENARIO--FIRST DETECTION

Before we actually derive any probability-of-detection expressions, it will be useful to design a test case to which the analytical expressions can be applied to provide a numerical example. Assume that three targets are in our field of view. Their characteristics are

	Target 1	Target 2	Target 3
P_∞	0.8	0.7	0.5
P_0/t_f	0.1	0.05	0.01

Thus, for example, the probability of detection for T_1 in the single-target case is

$$P(t) = 0.8\,[1 - \exp(-0.1t)]\,. \tag{4}$$

We now wish to consider the derivation of the expression for the probability of multitarget detection. As a preliminary analysis, let us assume that we are interested in the first detection of any target in an FOV in which M targets are present. If one considers the model given in Eq. 3, in which the search process is conducted through a set of glimpses with a constant probability of detection P_0^*, one obtains for the first detection

$$P(t) = 1 - \exp(-P_0^*\,t/t_f)\,, \tag{5}$$

where

$$P_0^* = \sum_{i=1}^{M} P_{0i} \tag{6}$$

and P_{0i} is the value of P_0 for the ith target. The underlying assumption for Eq. 6 is that P_0 is the probability for a given glimpse having the target within the foveal area times the probability of correctly detecting the target. In this case, P_0^* is the sum of the P_{0i} if they are located in separate foveal areas, and hence the probability of detecting a target is independent of detecting any other target.

By analogy with Eq. 1, we can assume that a fraction of the observer ensemble will never find the target. How to incorporate this into a form similar to Eq. 1 will depend heavily on which assumption one uses for the origin of P_∞.

It is interesting to note that each of the assumptions yields a different way to classify people in the multitarget acquisition process. We assume that we have M targets (labeled T_i) ordered so that the ith target is more obvious (has a larger P_∞) than the i+1th target. This convention will be used throughout this paper. Each target has associated with it a $P_{\infty i}$ (P_∞ for the ith target). Under Assumption 1, there would be M+1 classes of people: those who can see none of the targets, those who can see only the most obvious target, those who can see the two most obvious targets, etc. The probability of being in the ith class (which can see T_{i-1} but not T_i) is $P_{\infty i-1} - P_{\infty i}$. ($P_{\infty 0}$ equals 1 and $P_{\infty M+1}$ equals 0.)

Under Assumption 2, the probability of being able to see a particular target is independent of being able to see any other target. There exist 2^M classes. If one places the targets that an individual can detect into set C and the targets that an individual cannot detect into set D, the probability of being a member of a particular class is

$$\prod_{\substack{j=1 \\ T_j \in V}}^{M} P_{\infty j} \prod_{\substack{k=1 \\ T_k \in V}}^{M} (1 - P_{\infty k}) \qquad (7)$$

Finally, under Assumption 3, there is only one class of person; all observers can potentially detect all targets.

The nomenclature we shall use for the probability of detection is $P(t|M, M-M', V, T_J, J, t_i)$, where M is the number of targets in the FOV, M-M' is the total number of undetected targets in the FOV at time t_i, V is the set of undetected targets in the FOV at time t_i, T_J is the detected target with the least value of P_∞, and J is the ranking of the target such that $P_{\infty i} \geq P_{\infty J}$ if $i < J$, and $P_{\infty i} \leq P_{\infty J}$ if $i > J$.

For first detection probability starting at time 0, we have $P(t|M, M, V, \emptyset, 0, 0)$; we abbreviate this as $P(t|M, V)$.

Under Assumption 1, the rate of detection will depend on which of the M+1 classes of people the observer belongs to. Given that the M targets are ranked in difficulty so that $P_{\infty i} > P_{\infty i+1}$, the probability of detection would be

$$P(t|M,V) = \sum_{i=1}^{M} \left\{ (P_{\infty i} - P_{\infty i+1}) \left[1 - \exp\left(-\sum_{j=1}^{i} P_{0j} \cdot t \right) \right] \right\} \tag{8}$$

where

$$P_{\infty M+1} = 0.$$

It is interesting to note that $P(t=\infty)$, i.e., the fraction of observers who eventually find a target is equal to the fraction who could find the most obvious target. Adding on less obvious targets affects the rate of acquisition but not the final percentage of target acquirers. Using our standard numerical example quoted at the beginning of this section, we have

$$\begin{aligned} P(t|3, \{T_1, T_2, T_3\}) = {} & 0.1[1 - \exp(-0.1t)] + 0.2[1 - \exp(-0.15t)] \\ & + 0.5[1 - \exp(-0.16t)], \end{aligned} \tag{9}$$

i.e., 10 percent of the people detect only T_1 at a rate of 0.1 sec^{-1}, 20 percent can detect either T_1 or T_2 at a rate of 0.15 sec^{-1}, and 50 percent can detect all the targets at a rate of 0.16 sec^{-1}.

Under Assumption 2, there are 2^M classes of people vis-à-vis their ability to ultimately detect the M targets. All targets are undetected and hence in set V. To facilitate the mathematical expression for the probability of detection, we introduce a new function X(M, V, $t-t_i$, g), where M, V, and t_i have been defined previously and g is a parameter such that

$$X(M, V, t-t_i, g) = \sum_{\substack{J_1 = 1 \\ T_{J_1} \in V}}^{M} \sum_{\substack{J_2 = J_1 \\ T_{J_2} \in V}}^{M} \cdots \sum_{\substack{J_g = J_g - 1 \\ T_{J_g} \in V}}^{M} \left\{ \prod_{k=1}^{g} P_{\infty j_k} \prod_{\substack{L=1 \\ L \neq J_1 \ldots J_g \\ T_{J_L} \in V}}^{M} (1 - P_{\infty L}) \left[1 - \exp\left(-\sum_{k=1}^{g} P_{0 j_k} (t - t_i)/t_f \right) \right] \right\} \qquad (10)$$

For first detection $t_i = 0$, and all T_j are elements of V; we can abbreviate X(M, V, $t-t_i$, g) to X(M, V, t, g). The explanation of the function X(M, V, t, g) is straightforward. It represents the probability of detection of all classes of people who can detect exactly g out of the M targets; for each class that can detect T_{J_1}, T_{J_2}, ... T_{J_g}, the probability that one is a member is

$$\prod_{k=1}^{g} P_{\infty J_k} \prod_{\substack{L=1 \\ L \neq J_1 \ldots J_g \\ T_{J_L} \in V}}^{M} (1 - P_{\infty L}) \; ,$$

and the rate of detection is

$$\sum_{k=1}^{g} P_{0_{J_k}} (t - t_i)/t_f \, .$$

With the expression in Eq. 10, the probability of detection under Assumption 2 is

$$P(t \mid M, V) = \sum_{i=1}^{M} X(M, V, t, i) . \tag{11}$$

Since targets are independent, the probability in infinite time is

$$P(t = \infty) = 1 - \prod_{i=1}^{M} (1 - P_{\infty i}) . \tag{12}$$

For the standard example we have chosen with three targets, there are eight classes of observers. Our expression for P(t) has seven terms (those observers who cannot detect any target do not contribute):

$$\begin{aligned} P(t \mid 3, \{T_1, T_2, T_3\}) = {} & 0.28[1 - \exp(-0.16t)] + 0.28[1 - \exp(-0.15t)] \\ & + 0.12[1 - \exp(-0.11t)] + 0.07[1 - \exp(-0.06t)] \\ & + 0.12[1 - \exp(-0.1t)] + 0.07[1 - \exp(-0.05t)] \\ & + 0.03[1 - \exp(-0.01t)] . \end{aligned} \tag{13}$$

The first term is for that class of people who can find all the targets, the next three terms represent those who can find two of these targets, and the last three terms are for people who can find only one target.

Finally, we must consider the case where P_∞ is not due to a lack in any individual member of the observer ensemble, but where search gets ineffective as time passes (Assumption 3).

In that case, the probability of detection is simply

$$P(t \mid M, V) = P_\infty^* [1 - \exp(-P_0^* t / t_f)] , \tag{14}$$

where

$$P_0^* = \sum_{i=1}^{M} P_{0i} \ . \tag{15}$$

Additional assumptions are needed to calculate P_∞^*. Let us make the following unphysical approximation: Single-target search is effective with an arrival rate of P_{0i} until $t = t_0$ for a given scene, when it becomes totally ineffective. (This approximates the actual case where search becomes less effective as time progresses). In that case, for the ith target

$$P_{\infty i} = 1 - \exp(-P_{0i} t_0 / t_f) \ . \tag{16}$$

The probability of not finding the target by t_0 is

$$1 - P_{\infty i} = \exp(-P_{0i} t_0 / t_f) \ . \tag{17}$$

The probability of not finding any target by t_0 is

$$1 - P_\infty^* = \prod_{i=1}^{M} \exp(-P_{0i} t_0 / t_f) = \exp(-P_0^* t_0 / t_f) \ , \tag{18}$$

and hence

$$P_\infty^* = 1 - \exp(-P_0^* t_0 / t_f) \ . \tag{19}$$

But this is just the P_∞ one would have expected for a single-target acquisition process where $P_0 = P_0^*$. Thus, the multitarget case looks identical to the single-target acquisition process where the arrival rate P_0^* is given by Eq. 15, and P_∞^* is given by

$$P_\infty^* = 1 - \prod_{i=1}^{M} (1 - P_{\infty i}) . \tag{20}$$

Thus,

$$P(t) = P_\infty^* [1 - \exp(-P_0^* t/t_f)] . \tag{21}$$

It is interesting to note that Eq. 16 predicts that for small P_{0i}

$$P_{\infty i} \approx \frac{t_0}{t_f} P_{0i} , \tag{22}$$

i.e., that $P_{\infty i}$ is linearly dependent on P_{0i}. As stated in our section on single-target acquisition, this has been empirically noted in field tests analyzed by the CNVEO model.

In the standard three-target numerical example, this would yield:

$$P(t \mid 3, \{T_1, T_2, T_3\}) = 0.97[1 - \exp(-0.16t)] . \tag{23}$$

Figure 1 gives the results from the example calculated in Eqs. 9, 13, and 23. While the example worked out in the text shows differences for the different assumptions, the differences are most dramatic if several targets exist, each with low P_∞. For example, if we have five targets with P_∞ equal to 0.2 and $P_0/t_f = 0.1$, the probability-of-acquisition curves shown in Fig. 2 are obtained.

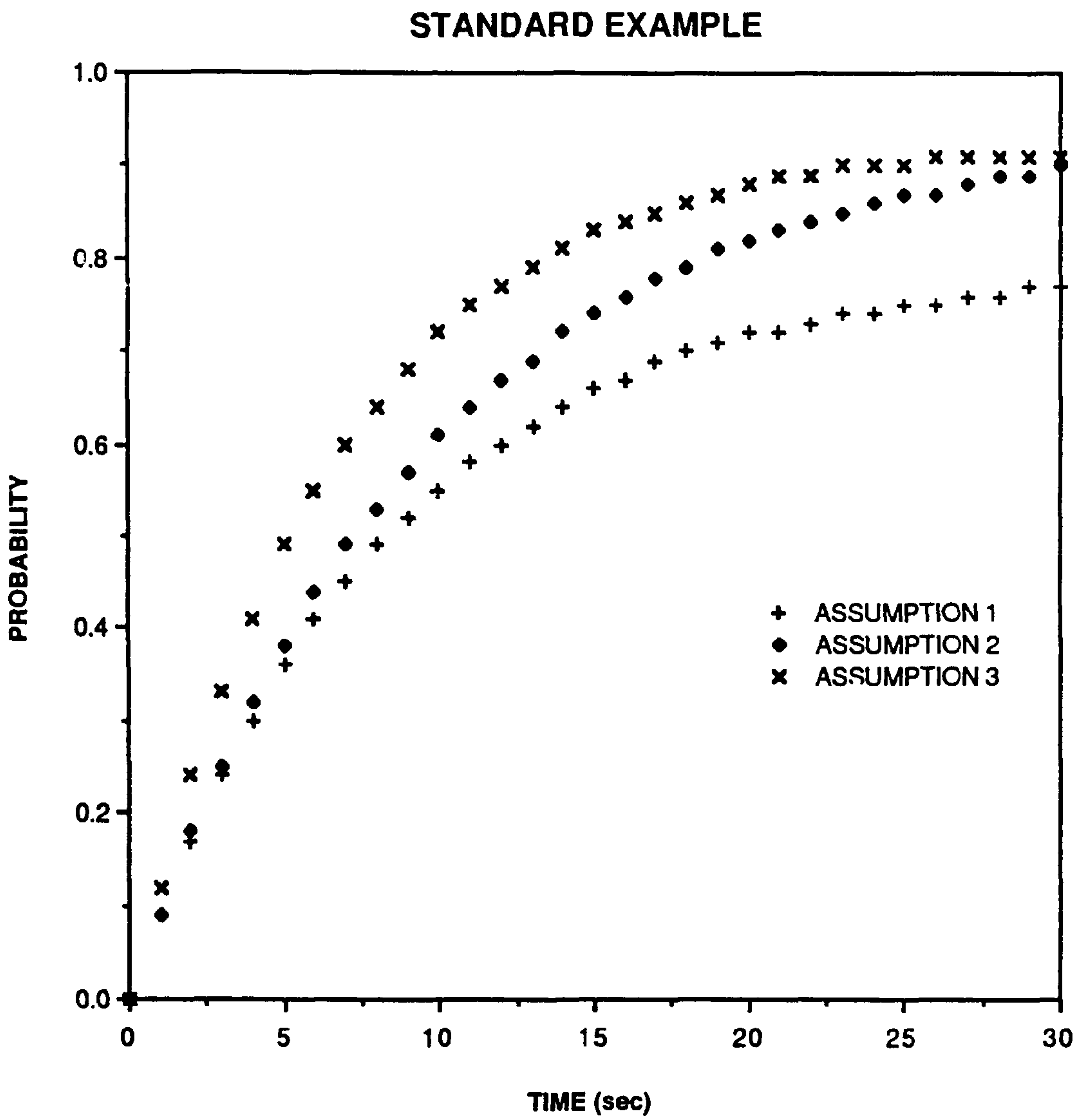

FIGURE 1. Cumulative probability distribution for three targets as described in the text.

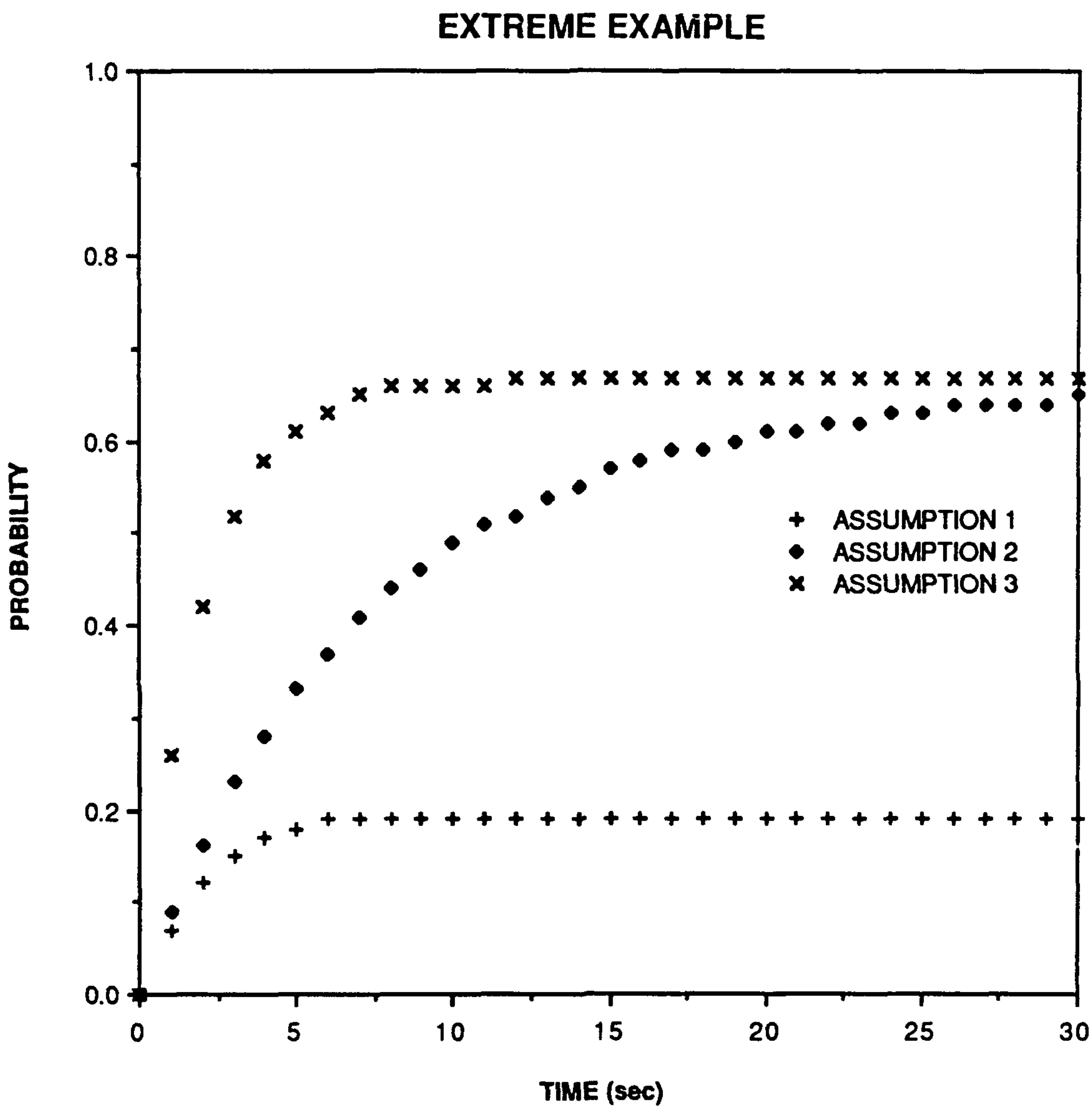

FIGURE 2. Cumulative probability distribution for five identical targets with $P_{\infty i}$ = 0.2 and P_{0i} = 0.1, illustrating dramatic differences as a result of the choice of assumption.

C. MULTITARGET ACQUISITION--MULTIPLE DETECTION

Often one does not complete the FOV search when the first target is acquired, so we must now consider the acquisition times for several targets.

The key to understanding the multiple-detection FOV search model is to realize that a cumulative probability distribution of the form

$$P(t) = 1 - \exp\left(-\frac{P_0}{t_f} t\right) \tag{24}$$

has the important property that

$$P(t \mid A) = 1 - \exp\left[-\frac{P_0}{t_f}(t - t_1)\right], \tag{25}$$

where A is the event that the target has not been found by time t_1. Equation 25 states that if the target has not been found by time t_1, it is equivalent to starting the process again, i.e., the probability that the target is found in the next Δt is $P_0 \Delta t/t_f$, just as it has been throughout the process. (In actual combat modeling, the beginning of the search for the second target would occur not at the detection of the first target but when one has finished with the first target as one chooses.)

The effect on multitarget acquisition is important. Assume that we have two targets with both $P_{\infty 1}$ and $P_{\infty 2}$ equal to unity; the probability distribution for the time for first detection is then

$$P(t \mid 2, \{T_1, T_2\}) = 1 - \exp\left[\left(-\frac{P_{01} + P_{02}}{t_f}\right) t\right]. \tag{26}$$

Assume that Target 1 was found at t_1; the probability distribution for finding Target 2 is then

$$P(t \mid 2, 1, \{T_2\}, T_1, 1, t_1) = 1 - \exp\left[-\frac{P_{02}}{t_f}(t - t_1)\right], \qquad (27)$$

where the notation for $P(t|M, M\text{-}M', V, T_J, J, t_i)$ is given in the previous section. Similarly, if one assumes that Target 2 was found at t_1, the probability distribution for finding Target 1 is

$$P(t \mid 2, 1, \{T_1\}, T_2, 2, t_1) = 1 - \exp\left[-\frac{P_{01}}{t_f}(t - t_1)\right]. \qquad (28)$$

If which target was detected at t_1 is unknown, the new process must be evaluated as the sum of probabilities that Target 1 or Target 2 was found. If a target was found at t_1, the probability P1 that the first target was the one detected is

$$P1 = \frac{P_1(t_1)}{P_1(t_1) + P_2(t_1)}, \qquad (29a)$$

and the probability P2 that the second target was the one that was first found is

$$P2 = \frac{P_2(t_1)}{P_1(t_1) + P_2(t_1)}, \qquad (29b)$$

where $P_1(t_1)$ and $P_2(t_1)$ are the detection probabilities for the single Targets 1 and 2, respectively. The probability for the second target acquisition is

$$P(t \mid t_1) = P_2\left\{1 - \exp\left[-\frac{P_{01}}{t_f}(t - t_1)\right]\right\} + P_1\left\{1 - \exp\left[-\frac{P_{02}}{t_f}(t - t_1)\right]\right\}, \qquad (30)$$

where $P(t|t_1)$ is the probability of the second acquisition when all that is known is that the first acquisition of some target occurred at time t_1.

How one incorporates $P_{\infty i}$ will once again depend on why one assumes that nonunity values of $P_{\infty i}$ occur.

Several mechanisms can affect the value of P_∞. Qualitatively, Assumptions 2 and 3 state that finding a target T_1 at time t_1 does not yield any information concerning the probability of ever finding any other target. However, Assumption 1 states that if one finds a target with a certain number of line pairs, one will certainly find all targets that have a greater number of line pairs.

A second effect is that if the first detection was of T_1 at time t_1, there is additional implicit knowledge that the observer has not found T_2 at time t_1. The probability that a person is a member of the class that will eventually find the target changes as a function of time. Obviously, if one has not found the target by time t_1, one is more likely to be a member of the class that never finds the target than one was at time $t = 0$. Mathematically for each target, the probability of ever finding the target, given that one has not found the target by time t_1, is

$$P_\infty(t_1) = \frac{P_\infty \exp\left(-\frac{P_0}{t_f} t_1\right)}{(1 - P_\infty) + P_\infty \exp\left(-\frac{P_0}{t_f} t_1\right)} . \tag{31}$$

Finally, if one assumes that search efficiency decreases as a function of time, one must ask whether finding a target somehow rejuvenates the process. It is possible to imagine that finding the target allows the process to restart psychologically.

Quantitatively, assume that we have M targets, M' of which have been found. The last target was found at time t_i; the least obvious found so far is T_J. The targets have been ordered in set V so that the detectability of T_i is greater (higher $P_{\infty i}$) than that of T_{i+1}.

Under Assumption 1, the number of classes has changed from M + 1 to M - J + 1 classes. An observer will certainly find T_i when $i < J$; the various classes of observers consist of those who can find no more targets with $i > J$, those who can only find T_{J+1}, those who can only find T_{J+1} and T_{J+2}, etc.

The probability of being in the class that can see the ith target but not the i+1th target is

$$P_{\infty i}(t_1) - P_{\infty i+1}(t_1)$$

and, by analogy with Eq. 31 and by writing $P_{\infty i}(0)$ for our former $P_{\infty i}$, we obtain

$$P_{\infty i}(t_1) - P_{\infty i+1}(t_1) = \frac{[P_{\infty i}(0) - P_{\infty i+1}(0)] \exp\left(-\sum_{L=J+1}^{L} \frac{P_{0L}(t_1)}{t_f}\right)}{\sum_{a=J}^{M} \left\{\left[P_{\infty a}(0) - P_{\infty a+1}(0)\right] \exp\left[-\sum_{L=J+1}^{a} \frac{P_{0L}(t_1)}{t_f}\right]\right\}} \tag{32}$$

This expression is obtained by considering the proportion of observers in each class who would be expected not yet to have found the target. For example, consider the case of two targets, T_1 and T_2, where T_1 is more observable than T_2. There are three classes at time t = 0: Class 1, those who can find no targets; Class 2, those who can find target T_1; and Class 3, those who can find T_1 and T_2. Each of these classes can be broken into subclasses based on performance as of time t_1. No one in Class 1 can find a target, and only one subclass exists. There are two subclasses in Class 2: (1) those who find a target T_1 by time t_1, and (2) those who do not. In Class 3 there are four subclasses: (1) those who find no targets by time t_1,

(2) those who find T_1, (3) those who find T_2, and (4) those who find both T_1 and T_2 by time t_1. Equation 32 consists of the proportion in each class who match the known situation at time t_1. If we assemble the targets not found by time t_i into a set V and the last detection was at t_1, we have

$$P(t \mid M, M-M', V, T_J, J, t_1) = \sum_{i=J}^{M} [P_{\infty i}(t_1) - P_{\infty i+1}(t_1)] \cdot \left\{1 - \exp\left[-\sum_{\substack{k=1 \\ T_k \in V}}^{i} \frac{P_{0k}(t-t_1)}{t_f}\right]\right\}, \quad (33)$$

where $P(t|M, M-M', V, T_1, J, t_1)$ is the probability of next detection, given that the targets not found are in set V, the least observable target found was T_J, and the last target was found at time t_1.

In the standard numerical example we have been using, if T_1 has been found at t_1, the probability of next detection is

$$\begin{aligned} P(t \mid 3, 2, \{T_2, T_3\}, T_1, 1, t_1) = \\ [P_{\infty 2}(t_1) - P_{\infty 3}(t_1)] \exp(-0.05t_1) \{1 - \exp[-0.05(t-t_1)]\} \\ + [P_{\infty 3}(t_1)] \exp(-0.06t_1) \{1 - \exp[-0.06(t-t_1)]\}, \end{aligned} \quad (34)$$

The other alternative explanations for P_∞ yield much simpler expressions. Under Assumption 2, the probability of finding a particular target is independent of finding any of the other targets. The only effect on P_∞ is that expressed in Eq. 31, i.e., as time goes by without finding a particular target, the probability of ever finding the target goes down. Thus, if the M-M' unfound targets are elements of set V and the last detection was at time t_1, we obtain Eq. 35 similar to Eq. 11:

$$P(t \mid M, M-M', V, T_J, J, t_1) = \sum_{i=1}^{M-M'} X(M, V, t-t_1, g) \qquad (35)$$

The term $X(M, V, t-t_i, g)$ is as defined in Eq. 10; the values of $P_{\infty i}$ must be replaced by $P_{\infty i}(t_1)$ from Eq. 31.

In our standard numerical example, if the first target is found at time t_1, the probability of the next detection as a function of time is

$$\begin{aligned} P(t \mid 3, 2, \{T_2, T_3\}, T_1, 1, t_1) = \; & P_{\infty 2}(t_1) P_{\infty 3}(t_1) \{1 - \exp[-0.06(t-t_1)]\} \\ & + P_{\infty 2}(t_1)[1 - P_{\infty 3}(t_1)]\{1 - \exp[-0.05(t-t_1)]\} \qquad (36) \\ & + P_{\infty 3}(t_1)[1 - P_{\infty 2}(t_1)]\{1 - \exp[-0.01(t-t_1)]\}, \end{aligned}$$

where

$$P_{\infty 2}(t_1) = \frac{0.7 \exp(-0.05 t_1)}{0.7 \exp(-0.05 t_1) + 0.3} \qquad (37)$$

and

$$P_{\infty 3}(t_1) = \frac{0.5 \exp(-0.01 t_1)}{0.5 \exp(-0.01 t_1) + 0.5} . \qquad (38)$$

Finally, if the cause of P_∞ is the drop in search efficiency as a function of time, an assumption must be made concerning the effect on the human psyche of finding a target at time t_1. If the finding of a target restarts the process and causes a person to search as efficiently at time $t_i + \Delta t$ as at time Δt, the values of $P_{\infty i}$ remain constant as a function of time. Thus if M-M' targets are left in set V, we have

$$P(t \mid M, M-M', V, T_J, J, t_1) = P_\infty^* \left\{ 1 - \exp\left[-\frac{P_0^*}{t_f}(t - t_1) \right] \right\}, \qquad (39)$$

where

$$P_{\infty i} = 1 - \exp(-P_0 t_0 / t_f) , \tag{40}$$

$$P_\infty^* = 1 - \prod_{\substack{i=1 \\ T_i \in V}}^{M} (1 - P_{\infty i}) , \tag{41}$$

and

$$P_0^* = \sum_{\substack{i=1 \\ T_i \in V}}^{M} P_{0i} \ . \tag{42}$$

On the other hand, if a person's search efficiency continues to deteriorate with time despite having found a target, the values of $P_{\infty i}$ used in Eq. 39 must be changed. The new values of P_∞ are lower than those in Eq. 19:

$$P_{\infty i} = 1 - \exp\left[- \frac{P_{0i}}{t_f} (t_0 - t_1) \right] . \tag{43}$$

This is only defined for $t_1 < t_0$, because the person has t_1 less than t_0 seconds $(t_0 - t_1)$ before he effectively gives up the search. Whether Eq. 40 or 43 is correct (whether the search process rejuvenates or continues to deteriorate) is unknown; a method to determine which is correct from field test data is discussed later in this paper.

Assuming that the process rejuvenates, we can calculate our standard numerical example. If Target 1 was detected at time t_1, the time for next detection is

$$P(t \mid 3, 2, \{T_2, T_3\}, T_1, 1, t_1) = 0.85\,\{1 - \exp[-0.06\,(t - t_1)]\}\,. \qquad (44)$$

In Eqs. 33, 35, and 39 for Assumptions 1, 2, and 3, respectively, we assume that it is known which targets have been acquired. If this is not so, one must take summations of the probabilities of detection, given a set of found targets, times the probability of that set of targets being found. A preliminary example of this was given in Eqs. 28-30; further development of this is outside the scope of the paper.

D. SUMMARY

In the results obtained for field-of-view search in a multitarget environment, we have seen that the single-target model contains two parameters: P_0, the glimpse probability for those members of the normal observer ensemble who can find the target; and P_∞, the fraction of the normal ensemble who can ever find the target. While the physical motivation for P_0 is straightforward and easily transferable to the multitarget environment, the origin and motivation for P_∞ remain unknown. Three possible explanations of P_∞ are given in the text. Expressions for the probability of first detection are then developed for each of the three possibilities. Expanding the problem to the case where M' out of M targets have been found introduces additional complications, essentially because P_∞ changes when one is given that M' specific targets have been found and that M-M' targets have not. In the next section, we discuss implementing this model in field-of-regard (FOR) search.

III. FIELD-OF-REGARD SEARCH

A. OVERVIEW OF CNVEO MODEL

In the CNVEO model, the field of regard (FOR) is divided into a discrete number of fields of view (FOVs). Search occurs systematically through the FOR; each FOV is scanned for t_0' seconds. The entire FOR scan takes nt_0' (or t_s) seconds, where n equals the number of FOVs.

Assume that the single target has a P_∞ equal to 1. In that case, the probability that the target is found in t_s seconds (of which t_0' was spent with the target in the FOV) is

$$P_s = P(t_s) = [1 - \exp(-P_0 t_0'/t_f)] . \qquad (45)$$

After m scans, the probability that the target is found is

$$P(m) = [1 - (1 - P_s)^m] . \qquad (46)$$

If one introduces a nonunity value of P_∞, this gives

$$P(m) = P_\infty [1 - (1 - P_s)^m] . \qquad (47)$$

For small values of P_s, this can be approximated as

$$P(m) = P_\infty [1 - \exp(-P_s m)] \qquad (48a)$$

or

$$P(t) = P_\infty [1 - \exp(-P_s\, t/t_s)] \qquad (48b)$$

Note that Eqs. 48a and 48b are valid only for small P_S, as given in Eq. 45.

B. MULTITARGET ACQUISITION--FIRST DETECTION

The multitarget detection scenario closely follows the single-target analysis. We start by assuming that the targets all have $P_{\infty i}$ and are randomly distributed through the FOR. Each target will hence be in the FOV for t_0' seconds for every scan of duration t_S seconds. In that case, the probability that any particular target will have been found at the end of scan P_{Si} is

$$P_{si} = 1 - \exp(-P_{0i} t_0' / t_f) \tag{49}$$

The probability that one or more of the M targets has been found at the end of the scan is

$$P_s^* = 1 - \prod_{i=1}^{M} (1 - P_{si}) . \tag{50}$$

The resulting probability of detection (looking for M targets in m scans) would be

$$P(m \mid M, V) = [1 - (1 - P_s^*)^m] \tag{51}$$

or

$$P(t \mid M, V) = [1 - \exp(- t P_s^* / t_s)] \tag{52}$$

for small P_S*.

Introducing a nonunity $P_{\infty i}$ for each of the targets affects the FOR target acquisition process much as it affected the FOV search process. If $P_{\infty i}$ is due to a fraction of the populace who cannot find a target because they need more line pairs

(Assumption 1), we must divide the population into groups: those who cannot find any target, those who can only find one target, etc. As in Eq. 8 for FOV search, we have for FOR search

$$P(m \mid M, V) = \sum_{i=1}^{M} (P_{\infty i} - P_{\infty + 1}) \left\{ 1 - \left[\prod_{j=1}^{i} (1 - P_{sj}) \right]^{m} \right\} \tag{53}$$

or

$$P(t \mid M, V) = \sum_{i=1}^{M} (P_{\infty i} - P_{\infty i + 1}) \left[1 - \exp\left(-t \sum_{j=1}^{i} P_{sj}/t_s \right) \right] . \tag{54}$$

If, instead, the probability that an individual will ever find a particular target is independent of his ever finding some other target (Assumption 2), as in Eq. 11 for FOV search, the probability for FOR search is

$$\begin{aligned} P(m \mid M, V) = & \prod_{i=1}^{M} P_{\infty i} \left\{ 1 - \left[\prod_{j=1}^{M} (1 - P_{sj}) \right]^{m} \right\} \\ & + \sum_{j=1}^{M} \prod_{\substack{i=1 \\ i \neq j}}^{M} P_{\infty i} (1 - P_{\infty j}) \left\{ 1 - \left[\prod_{k \neq j}^{M} (1 - P_{sk}) \right]^{m} \right\} \ldots \end{aligned} \tag{55a}$$

or

$$P(t \mid M, V) = \sum_{i=1}^{M} X'(M, V, t, i) , \tag{55b}$$

where $X'(M, V, t, i)$ is identical to $X(M, V, t, i)$ except that P_{0i}/t_f is replaced by P_{si}/t_s.

Finally, if P_∞ is due to a decrease in search efficiency with time, we have a much more complicated situation. We have previously assumed that the deterioration in search efficiency is due to both discouragement at not finding a target and mental fatigue. Until now, when going from the single-target FOV search to the multitarget FOV search, we have assumed that the deterioration in search efficiency is the same in either case. However, how do we extrapolate the parameters of FOR search from FOV search data?

We can consider two extreme cases. In the first, we can assume that the search efficiency deteriorates because of the length of time a particular FOV has been in view cumulatively during the FOR search process. In that case, the P_∞ values remain the same and we have

$$P(m) = P_\infty^* [1 - (1 - P_s^*)^m] \tag{56}$$

or

$$P(t) = P_\infty^* [1 - \exp(- P_s^* t / t_s)] , \tag{57}$$

where

$$P_\infty^* = 1 - \left[\prod_{i=1}^{M} (1 - P_{\infty i}) \right] \tag{58}$$

and

$$P_s^* = \sum_{i=1}^{M} P_{si}^* . \tag{59}$$

On the other hand, if the deterioration in search efficiency continues even though the target is not in the FOV, the new $P_{\infty i}$ will be much lower for those targets that come into view later in the scan than for those that come into view earlier. This greatly complicates the problem, and we shall not consider the problem further here; we discuss possible field tests that could clarify this issue in a later section.

C. MULTITARGET ACQUISITION--MULTIPLE DETECTION

The analysis done for the FOV search with multitarget acquisition is applicable to the FOR search. Once again, the nature of the process is such that if one has found a target at t_1, the process begins again, and the probability of finding a particular target in the next Δt is still $P_0 \Delta t/t_f$, as it was in the beginning of the process.

Without going into further analysis, the expressions developed for FOV next-detection search are in general correct for FOR next-detection with the substitution of P_{si}/t_s for P_{0i}/t_s. To be specific for FOR multitarget multiple detection, if Assumption 1 is correct, Eq. 33 is correct for FOR search with P_{0k}/t_f replaced by P_{sk}/t_s. If Assumption 2 is correct, Eq. 35 is correct with $X'(M-M', V, t-t_1, i)$ replacing $X(M-M', V, t-t_1, i)$. Finally, under Assumption 3, Eqs. 39-42 are correct with P_{0i} replaced by P_{si} and t_f replaced by t_s. The discussion concerning the effects of FOR search and target acquisition on search efficiency is still relevant here.

IV. BATTLEFIELD MODEL

While the expressions in Chapters II and III are quite involved, their implementation in a battlefield model, such as the Army's battalion-level models, CASTFOREM and CARMONETTE, is straightforward. In this section, we discuss the method of implementing the single-target acquisition model in a computer-run battlefield model. We then consider the multitarget FOV and FOR cases, with special emphasis on how the different methods of calculating P_∞ affect the implementation. We commence with a study of the basic principles involved in implementing target acquisition in the battlefield models.

A. BASIC PRINCIPLES

Several basic principles apply, no matter which specific model one implements. First of all, some of the models suggest that observers can be grouped into classes. For example, in the CNVEO model, it is assumed that a fraction of the population P_∞ can find a particular target at rate P_0/t_f, while a fraction $(1-P_\infty)$ cannot. Before the target acquisition process commences, a particular observer can be assigned to the class to which he will belong as the program progresses. One possible way to implement this, to which we resort several times in this chapter, is by drawing a random number x with a constant probability distribution between 0 and 1. If $x < P_\infty$, we assign the observer to the class of people who can find the target; if $x > P_\infty$, we assign him to the class of people who cannot. A similar method for multiple classes is possible when needed.

A second basic principle is that to determine the time of acquisition for an observer who can find the target and has a single-glimpse acquisition probability P_0, a second random number y should be drawn. This number can then be input into the expression

$$t = -\ln(1 - y) / (P_0/t_f) \tag{60}$$

to obtain the time for acquisition. (Equation 60 is obtained by inverting Eq. 3 for time.)

The third principle involves the multitarget acquisition process. If one has several acquisition processes going on simultaneously, one must either combine these processes into a single process (as described later in the text) or draw separate random numbers for each process. If one mistakenly chooses only one random number for both separate processes, one obtains the unphysical result that the target with the higher single-glimpse acquisition rate is always found before a target with the lower single-glimpse acquisition rate. The nature of the random processes demands that the less obvious target should be acquired before the more obvious target a fraction of the time. We are now prepared to discuss implementing target acquisition in specific scenarios.

B. SINGLE-TARGET FOV ACQUISITION

In the CNVEO single-target FOV acquisition model, there are two classes of people: those who can find the target and those who cannot. The ratios of those who can and those who cannot to the entire population are P_∞ and $1-P_\infty$, respectively; the single-glimpse probability for those who can is P_0.

By the principles stated in the previous section, two random numbers between 0 and 1 should be drawn: one that determines whether the observer can find the target, and a second that determines when the observer acquires the target, given that he does acquire it. In this method Eq. 60 would be used to get the actual acquisition time. An alternative method is possible in which only one number x needs to be drawn. If the number x is between 1 and P_∞, the observer does not find the target and the time to acquire t_1 is infinite. If the number x is between 0 and P_∞, one uses the target to determine the acquisition time by renormalizing x; thus,

$$t = -\ln(1 - x/P_\infty)/(P_0/t_f) . \tag{61}$$

The acquisition time can then be used in the battlefield-model simulation in two ways. If there is infinite time to search the FOV, the value of t_1 is given by Eq. 61. However, if there is limited time t_0 to search the FOV, an acquisition time larger than t_0 is equivalent to the target's never being found. In that case, t_0 seconds pass in the model and the target remains undetected.

C. MULTIPLE-TARGET FOV ACQUISITION

In the battlefield models, the placement of both targets and observers is known. Thus, all search is essentially FOV search; even when the FOR is larger than the FOV, at any one time the FOV is known for the observer. We thus emphasize implementing multitarget acquisition in a single FOV.

Assume that one has M targets in the FOV. As we showed in Chapter II, there are several models for the value of P_∞ to determine which targets can be detected. Assumption 1 has M+1 classes of people: one class can find no targets, one class can find the most obvious target, one class can find the two most obvious targets, etc. In this case, the probability of being in the i+1th class (who can see exactly i targets) is $P_{\infty i} - P_{\infty i+1}$ (Eq. 7). The assignment to a class can be done by a single draw of a random number x; if the number x is such that $P_{\infty i} > x > P_{\infty i-1}$, the observer is a member of that class.

Assumption 2 has 2^M classes where the probability of being able to detect T_i is independent of being able to detect T_j.

In that case, M random numbers can be drawn, and the ith number determines whether or not the observer can detect the ith target.

Assumption 3 has only one class of observer. All targets are potentially detectable by all observers; P_∞ is due to the deterioration of all observers' search efficiency with time. No random number need be drawn to determine the class of the observer.

Once we have determined the class of the observer in the battlefield model, he stays in this class for the duration of the program. (Obviously, many simulations need to be run to obtain results relevant to a genuine normal observer ensemble.) The next step is to determine the time it takes the observers to find the various targets. There are two methods possible here for Assumptions 1 or 2. If the observer can detect targets that are elements of the set V (which is a subset of the set of all targets), then

$$P_0^* = \sum_{\substack{i=1 \\ T_j \in V}}^{M} P_{0i} . \tag{62}$$

Draw a random number y, and the time for first detection t_1 is

$$t_1 = -\ln(1 - y)/(P_0^*/t_f) . \tag{63}$$

An alternative is to draw a separate random number for each of the targets in set V. The detection times are then

$$t_i = -\ln(1 - y)/(P_{0i}/t_f) , \tag{64}$$

and the smallest t_i is the first detection t_1. This method is superior since it permits the program to determine which target was found. As was stated for single-target acquisition, if no target can be found, t_1 is infinite; similarly, if we limit the acquisition time to t_0 in the FOV, we assign a "target not found" condition if $t_1 > t_0$. A time of t_0 seconds must be charged to the program, during which it tries and fails to find the target. Subsequent detections are determined by the remaining acquisition times.

Under Assumption 3, the proper equation to use is

$$t_1 = -\ln(1 - y/P_\infty^*)/(P_0^*/t_f), \tag{65}$$

where

$$P_\infty^* = 1 - \prod_{i=1}^{M} (1 - P_{\infty i}) \tag{66}$$

for $y < P_\infty^*$. If $y > P_\infty^*$, the target is never found. Alternatively, to determine which target is found one can draw L random numbers (where L is the number of observable targets for a particular class of observers) and calculate the arrival times by

$$t_i = -\ln(1 - y/P_{\infty i}) / (P_{0i}/t_f), \tag{67}$$

The smallest t_i becomes t_1. Subsequent detections are determined by the remaining acquisition times.

In summary, first-detection acquisition times are fairly easy to obtain in the multitarget environment. One first determines what class of observer is manning a particular sensor; that assignment remains for the duration of the program. This is done by a single-number or multiple-number draw. The number of classes one divides the observers into depends on the assumptions one uses for the origin of P_∞. Finally, given L targets, one draws L random numbers and computes the detection times; alternatively, one may combine the L targets into a single process and draw one random number.

Two pitfalls must be avoided in these methods. First, one cannot use the same random number for both the determination of class and the determination of acquisition time. Second, one cannot use a single random number and still look at the targets separately.

This is best explained through an example. We use the standard multitarget example that we used in Chapter II with $P_{\infty 1} = 0.8$, $P_{\infty 2} = 7$, and $P_{\infty 3} = 0.5$. Under Assumption 1, we draw a single number x. If $x > 0.8$, the observer can find no targets. If $0.8 > x > 0.7$, he can find T_1 and T_2, and if $x < 0.5$ he can find T_1, T_2, and T_3. Under Assumption 2, three numbers will be drawn: x_1, x_2, and x_3. If $x_1 > 0.8$, Target 1 cannot be found; if $x_1 < 0.8$, it can. If $x_2 > 0.7$, Target 2 cannot be found; if $x_2 < 0.7$, it can, etc. For Assumption 3, all three targets can be detected; no number need be drawn. Finally, one or L random numbers are drawn, and the acquisition times are computed.

If the number to determine the class were also used to determine the acquisition time, an incorrect answer would be obtained. For example, under Assumption 1 if $x = 0.75$, we would determine that only Target 1 can be found and that it takes a relatively long time to find it. There would be no possibility of determining that only Target 1 can be found and that it takes a short time to find it, which is contradictory to the model. Similarly, if a single random number were used to calculate the acquisition times for T_1, T_2, and T_3 separately and the minimum detection time were taken, the target with the largest P_{0i} would always be found first; this, too, is nonphysical and must be avoided.

In the CASTFOREM and CARMONETTE models, one always knows which targets are detected; hence, none of the complications of computing the probability of which target was found (Eqs. 29-30), given that a target was found, are relevant. Similarly, the model chooses which class a particular observer belongs to at the beginning of the program; there is thus no need to recompute these probabilities on the basis of the observers' performance (Eq. 31).

For FOR detection, there arises the question of what the search pattern is. Since the particular FOV being searched at any one time is known, the more general equations for FOR search are not needed. However, it is interesting to note that Eqs. 47 and 48 for small P_S can be shown to be valid approximations in both systematic and random search patterns. Thus, if one does not "know" the particular FOV being searched, the equations for FOR search may apply regardless of search strategy.

V. FIELD TESTS AND EXPERIMENTS

The models presented in this paper are quite tractable mathematically. Experimental data is needed to validate the models and evaluate the particular algorithms the models have chosen. In addition, for the models to be useful we must understand how they can be used to evaluate actual field tests. This will be the subject of this chapter.

A. VALIDATING EXPERIMENTS

We wish to emphasize from the outset that some of the experiments needed to validate the models are relatively inexpensive and simple to set up. While data from previously conducted field tests is useful, some small laboratory experiments may provide important information on the nature of multitarget acquisition.

1. Classes of Observers

The major issue raised in this paper involves the nature of P_∞. Is it due to a fraction of the population needing more resolution than was available (Assumption 1), is it due to a fraction of the population not recognizing the target against the clutter (Assumption 2), or is it due to deterioration in search efficiency as a function of time (Assumption 3)? Several experiments, suggested below, would determine the answer.

For the first experiment, take three groups of N random observers. The first group should attempt to find a single target in realistic terrain in several displays as a function of time. Thus, for each display, the time it takes each of the N observers to acquire the target is noted. Values of P_0 and P_∞ for each target-terrain orientation are obtained. The second group should follow the same acquisition process on the same displays, except that the target is located in a different spot. New values of P_0' and P_∞' for that target-background combination are found. Finally, the third group looks at the display when both targets are present, and this group's attempts to acquire both targets (P_0'' and P_∞'') are recorded.

If Assumption 1 is correct, P_∞'' should equal the maximum of P_∞' and P_∞ for each picture. If the more obvious target cannot be obtained by a fraction of the people, they certainly cannot obtain the less obvious target. Moreover, no individual should be able to find the "less-visible" target and not the "more-visible" one. This can be confirmed on a person-by-person evaluation of the members of the third observer group. On the other hand, Assumptions 2 and 3 would give values of P_∞'' greater than P_∞ and P_∞'; in particular,

$$P_\infty'' = P_\infty + P_\infty' - P_\infty P_\infty' . \qquad (68)$$

This, too, can be examined in the experiments.

To distinguish Assumption 3 from Assumptions 1 and 2, a second experiment can be performed on single-target displays. A group of observers is shown a set of displays on a particular day; those displays in which the observer cannot find the target in an essentially infinite time are recorded. After a long period of time, when memory has faded, the same displays should be shown again. Assumption 3 states that those observers who do not find the target the first time have a finite chance of finding the target the second time. Assumptions 1 and 2 state that they do not. This can be quickly determined.

2. Acquisition Rates

The model predicts that the rate of acquisition P_0^* increases when more targets are in the field of view by the equation

$$P_0^* = \sum_{i=1}^{M} P_{0i} \qquad (69)$$

for the M target in the FOV. Given the previous section, one could use the same multitarget experiment to determine if the rates of acquisition have increased as expected.

In addition, under Assumption 3, where the search efficiency deteriorated as a function of time, we questioned whether finding a target would rejuvenate the search process. From the first experiment in the previous section one can obtain values for when observers effectively ceased to obtain a target. By comparing the single-target and multitarget times, it would be interesting to see the lengths of time effective search appears to be occurring.

Moreover, all the models in this paper show that the interarrival times for target acquisition should increase in the multitarget scenario. For example, given two identical targets with an average time for acquisition for each alone of t_0, one would expect the first target to be obtained on average in $t_0/2$ seconds, while the second target should be obtained on average t_0 seconds later, or 3 $t_0/2$ seconds after the start of the search process. The varying acquisition time for the ith target has been observed in a recent thesis by Dubois.[6] The first experiment suggested in the previous section would provide a further confirmation.

B. FIELD TEST INTERPRETATION

One of the major values of the model in this paper is that it allows the multitarget acquisition process in field tests to be understood.

When interpreting the data, there are two ways to process it. One can, essentially, average the acquisition times for individual targets or several targets over a group of observers. While this is useful and valuable for evaluating systems, it should be noted that much detail is lost in averaging. Such details as

- Which observers are able to detect both T_i and T_j
- The interarrival time between finding T_i and T_j
- Whether classes of observers exist who consistently do better target acquisition than others

can be derived from the data. This can help in developing both a more representative group of observers to perform field tests and a higher quality of observer for actual assignment in military performance. Moreover, the application of this model to battlefield models allows an accurate simulation of real field tests to occur.

VI. CONCLUSION

A multitarget acquisition model has been developed as an extension of the CNVEO single-target acquisition model. The implementation of this model in battlefield combat simulations has been outlined. Finally, the use of this model to accurately simulate field tests and the use of simple experiments to validate the model have been suggested.

REFERENCES

1. W.R. Lawson, T.W. Cassidy, and J.A. Ratches, "A Search Prediction Model," Proceedings of the IRIS Specialty Group on Imaging, June 1978.

2. R. Flaherty and W. Lawson, "Laboratory Search and the Night Vision and Electro-Optics Laboratory Search Model," Proceedings of the IRIS Specialty Group on Imaging, January 1983.

3. I. Overington, Vision and Acquisition: Fundamentals of Human Visual Performance, Environmental Influences and Applications in Instrumental Optics, Crane Russak & Company, Inc., New York, 1976.

4. T.B. Morawski, C.G. Drury, and M.J. Kawan, "Predicting Search Performance for Multiple Targets," Human Factors, 22, 1980.

5. C.G. Drury, "Integrating Human Factors Models into Statistical Quality Control," Human Factors, 20, 1978.

6. L.M. DuBois, "Comparison of Time to Detect Definitions," M.S. Thesis at the Naval Postgraduate School, June 1986.